Modified Histogram Segmentation Bi-Histogram Equalization

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Abstract— Image enhancement is the widespread application of the image processing field. Conventional methods which are studied in contrast enhancement such as Histogram Equalization (HE) have not satisfactory results on many different low contrast images and they also cannot automatically handle different images. These problems result of specifying parameters manually in order to produce high contrast images. In this paper, Modified Histogram Segmentation Bi-Histogram Equalization (MHSBHE) is proposed. In this study, histogram is modified before segmentation to improve the input image contrast. The proposed method accomplishes multi goals of preserving brightness, retaining the shape features of the original histogram and controlling excessive enhancement rate, suiting for applications of consumer electronics. By this simulation results, it has been shown that in terms of visual assessment, Absolute Mean Brightness Error (AMBE), Peak Signal-To-Noise (PSNR) and average information content (entropy) the proposed method has better results compared to literature methods. The proposed method enhances the natural appearance of images especially in no static range images and the improved image is helpful in generation of the consumer electronic.

Keywords: Histogram Equalization, Histogram Segmentation, Image Contrast Enhancement.

1 Introduction

Artificial intelligence has significant effect in different domains such as data mining [1-7], pattern recognition [8-12], machine learning [13-19] and image processing [20-23]. One of the application of image processing is image enhancement [24]. In image contrast enhancement, numerous image enhancement techniques have been researched like a gray-level transformation techniques and histogram processing techniques. In the first group, these methods map the gray-level value in the image to the new one by using transformation function such as power-law transformation, logarithm transformation, etc. For example, in Ref. [25] proposed a method on the statistic image features. The proposed method which is a local, adaptive and multiscale takes the local average and local minimum/maximum in the window at the center of each pixel and then for each pixel identifies a transformation function. Another method in this group is on the 2D Taeger–Kaiser Energy Operator which is quadratic filter. This filter computes the average of the gray values at each pixel by the energy activity. A certain function transforms this value in order to enhance the pixel's contrast. After that the updated pixel is obtained by applying the reverse steps.

In histogram processing techniques, various studies have already been studied on histogram equalization. Histogram Equalization (HE) is a method in this application. This method is applied widely [26-28]. Achieving a uniform distributed histogram is the major aim of this method. Using the Cumulative Density Function (CDF) of the input image can lead to reach this goal [29]. The prominent drawback of HE is that it may cause to a faded looking, intensified noise and every undesirable objects. It is a verified fact that the mean brightness of the enhanced image is placed at the center of original image gray level regardless of its mean. This property is annoying characteristic in the number of application where brightness preservation is needed [25].

To solve the aforementioned problems different methods with different ability such as mean preserving Bi-Histogram Equalization (BBHE) [30] have been proposed. In BBHE, the histogram of the image divided into sub histogram based on the image mean then each sub histogram equalized, individually. Equal Area Dualistic Sub-Image Histogram Equalization (DSIHE) [31] is very similar to the BBHE, but the cutting point is median instead of the mean. Recursive Mean-Spread Histogram Equalization (RMSHE) [29] is an recursive method that splits each new histogram of the image recursively based on the mean of the original image. In [32] exposure based sub-image histogram equalization (ESIHE) method is proposed by Singh and Kapoor. This method is useful for low exposure image enhancement. In this approach the histogram is split into sub-histograms and the cutting point is calculated by the exposure threshold. Recursive exposure based sub-image histogram equalization (R-ESIHE) [33] calls ESIHE in recursive steps. This method continues until the value from computing the exposure of the histogram is under a certain value. K. Singh and et al. proposed another work as recursively separated exposure based sub image histogram equalization (RS-ESIHE) [33]. In this method, the algorithm recursively segregates the histogram of image based on the related exposure value. After that each generated sub-histogram is equalized, exclusively. In the another research study, they have also study on Median-Mean based Sub-Image Clipped Histogram Equalization (MMSICHE) [34] algorithm. This has two steps: In first step, median intensity value split the histogram of original image and in the second step, mean intensity value divide the generated sub-histograms. Finally, the algorithm equalize each clipped sub histograms.

Generally, methods based on the Histogram Equalization are grouped into two main groups: local and global [35]. In Global Histogram Equalization (GHE) [36], it is used the total image histogram for enhancement of input image. This method is good for equal frequency gray levels and it fails in image with very high frequency gray levels. Because the image contrast is limited in high frequency gray levels, therefore, it leads to considerable contrast lack for gray levels with lower frequency [35]. To solve this drawback, local histogram equalization (LHE) is proposed [37-39]. In block-overlap histogram equalization [40] which is a LHE method used a windows placed on each pixel of image and HE is implemented only on sub-image that are encompassed in this windows. Then, the gray level of center pixel of window is mapped for enhancement.

Shape preserving histogram modification [41] and Partially Overlapped Sub Block Histogram Equalization (POSHE) [42] are different LHE methods. The only different between the mentioned methods and block-overlap histogram equalization is that in shape preserving histogram modification instead of rectangular window, it is used connected components and level set while in POSHE method the block size is increased in horizontal and vertical coordinate by the constant step size not in one pixel similar to in block-overlap histogram equalization method. These approaches need a considerable computational cost and also it strengthens the noise of original image. Recently, combination of both LHE and GHE is proposed [43].

In this study, a Modified Histogram Segmentation Bi-Histogram Equalization (MHSBHE) is proposed. In this study, the histogram segmentation is modified based on average bins. The main contribution of MHSBHE is that it can handle images automatically with high brightness. Results of Simulation illustrate that MHSBHE outperforms recent existing methods in the literature in PSNR, entropy, AMBE and also visual assessment.

This paper is as follows: section 2 will describe MHSBHE. Experimental results will be explain in section 3 and conclusion will be discussed in section 4.

2 The Proposed Method

We introduce Modified Histogram Segmentation Bi-Histogram Equalization (MHSBHE) method in this section. MHSBHE is applied in three steps: histogram modification, histogram segmentation, sub-histogram equalization.

In first step, the histogram is modified before segmentation. In fact, this step is considerably helpful in the segmentation of histogram and is effective in brightness preservation. The past methods have not any modification in segmentation (Table 1).

In this way, the value of histogram bins is more than the average number of gray levels and they are confined to the threshold. The average value is calculated in (1) and (2):

$$Th_c = \frac{1}{L}\sum_{m=1}^{L} hist(m) \tag{1}$$

$$hist_c(m) = Th_c \qquad\qquad hist(m) \geq Th_c \tag{2}$$

Where $hist(m)$ and $hist_c(m)$ are the input and clipped histogram, respectively.

In the second step, an exposure threshold [32] is applied to compute severity image exposure. This step splits the modified image in two sub-images, under/over exposed sub-image. [0–1] is the normalized exposure value range. If this value is more than 0.5, it shows that the majority area of image is over-exposed and if this value is lower than 0.5 then image has majority of under exposed area. Contrast enhancement should be done in both cases. This value is formulated as

$$exposure = \frac{1}{L}\frac{\sum_{m=1}^{L} hist_c(m)\, m}{\sum_{m=1}^{L} hist_c(m)} \tag{3}$$

Where L is total gray levels number. In addition that parameter X_α (Eq. (4)) is introduced, which determines the gray level value threshold. By this parameter the input image is split into under/over-exposed subimages.

If the exposure value is lower/larger than 0.5 then X_α obtains a value of larger (lower) than $L/2$ for the range of 0 to L.

$$X_\alpha = L(1 - \text{exposure}) \tag{4}$$

Finally, in step three, HE is implemented on sub-histograms. In such process, the original image histogram is divided rely on the parameter of exposure threshold, X_α, as formulated in (4) and its results are I_{Low} sub-image from 0 to X_α gray level and I_{Up} sub-image from $X_\alpha + 1$ to $L - 1$ gray level. This is known as under/over exposed sub-images. $P_{Low}(k)$, $P_{Up}(k)$, $C_{Low}(k)$, and $C_{Up}(k)$ are related to Probability Density Function (PDF) and Cumulative Density Function (CDF) of these sub-images, respectively and they are defined in (5)-(8).

$$P_{Low}(k) = hist_c(k)/N_{Low}, \qquad k = 0 \ldots X_\alpha. \tag{5}$$

$$P_{Up}(k) = hist_c(k)/N_{Up}, \qquad k = X_\alpha + 1 \ldots L - 1. \tag{6}$$

$$C_{Low}(k) = \sum_{k=0}^{X_\alpha} P_{Low}(k), \tag{7}$$

$$C_{Up}(k) = \sum_{k=X_\alpha+1}^{L-1} P_{Up}(k), \tag{8}$$

Where N_{Low} and N_{Up} are pixels number in sub-images I_{Low} and I_{Up}, respectively.

Equalization is implemented on two sub-histograms, individually. For histogram equalization, the transfer functions can be defined as

$$F_{Low} = X_\alpha \times C_{Low} \tag{9}$$

$$F_{Up} = (X_\alpha + 1) + (L - X_\alpha + 1)\ C_{Up} \tag{10}$$

F_{Low} and F_{Up} are two transfer-functions which are applied in equalization of these sub-histograms, exclusively. Finally, these sub-images combine in one full image. The high quality image is generated by merging two transfer-functions.

3 Experimental Results

The simulation results of MHSBHE, are presented and the result of comparisons to six well-known literature works i.e. HE, BBHE [30], DSIHE [31], RMSHE [29], ESIHE [32] and R_ESIHE [33]. To analyze these methods, 400 test images are used. Two images, i.e. Road and Mass, are compared based on visual quality and the results are illustrated in Figs. 1-2.

To measure the function of MHSBHE, Entropy is introduced. It is one of the measure in order to calculate the image quality to evaluate enhanced image [33]. The value of Entropy shows the amount of information bring to the enhanced image. This mean that if the value of entropy is high, the amount of information that bring is greater. Eq. (11) calculates Entropy

$$Ent(img) = -\sum_{k=0}^{L-1} PDF(k) \, log PDF(k) \tag{11}$$

Where $PDF(k)$ shows PDF of image at intensity level k.

In addition that entropy is measured in units as bits and can be as a criteria of affluence of the image details. Referred to Shannon Entropy, this entropy measures the uncertainty related to image's gray levels. The higher amount of entropy shows that the enhanced image has high quality as well as richness of details.

To evaluate the performance of MHSBHE, AMBE [44] is used. AMBE is a useful in calculating the brightness preservation level. The AMBE between two input and improved image is computed as follow:

$$AMBE(In, Out) = |mean_{In} - mean_{Out}| \tag{12}$$

Where *In* and *Out* are input and enhanced image, respectively. Also, $mean_{In}$ and $mean_{Out}$ are the mean of the two original and enhanced image, respectively. If this difference is less, this shows that the improved image has preserved the brightness from the original image.

Lastly, P_{snr} measures the peak signal-to-noise of the enhanced image. Regarding to noise expanding problem during the enhancement, PSNR quantifies the quality of an enhanced image:

$$P_{snr}(I(c)) = \frac{10 \times log_{10}(L-1)^2}{MSE}, \tag{13}$$

3.1 Performance Assessment

For comparison, accuracy measurement is necessary between MHSBHE and literature work based on the PSNR, entropy and AMBE for 400 benchmark images. Table 2 shows quantitative analyses for two test images. MHSBHE produces highest values in most cases. Beside this comparison, MHSBHE implemented on 400 images on different databases such as USC-SIPI (Misc and Sequences), USF-DM, Astronomical images, Medical images, Miscelaneous and etc. The comparison results are presented in Table 3. As it can be seen in this Table, the proposed method, MHSBHE, has better results in all measurements.

Table 1. Quantitative analyses for six test images.

Image contrast enhancement methods	Implementation Steps
HE	1. HE
BBHE	1. HS based on the input image mean 2. HE
DSIHE	1. HS based on density function 2. HE
RMSHE	1. HS based on the input image mean, recursively 2. HE
ESIHE	1. HC based on the average number of intensity occurrence 2. HS based on exposure threshold 3. HE
R-ESIHE	1. HC based on the average number of intensity occurrence, recursively until predefined threshold 2. HS based on exposure threshold 3. HE
MHSBHE (proposed method)	1. Histogram Modification 2. HS based on exposure threshold 3. HE

3.2 Assessment of visual quality

Finally, the methods are compared based on image visual assessment. The enhanced images which are resulted after applying the MHSBHE and the mentioned method are demonstration in Fig. 1-2. As shown in these enhanced images, MHSBHE has better natural appearance and high contrast images.

Obviously, in Fig. 1 of Road image, it is shown that the MHSBHE image improves the Truck in the image, effectively. This enhancement obviously can be seen compared to other methods. In Fig. 2, by applying MHSBHE, an extreme contrast of the results in contrast enhancement as well as natural appearance, can be obviously observed in this figure. Results of other methods enhance the noise. However, by managing on over-enhancement, MHSBHE can reach to the desirable enhancement outputs.

Although the MHSBHE results in some images are visually comparable to literature approaches, MHSBHE gives considerably the highest PSNR, entropy and AMBE for such test images. From both quality and quantity simulation results, it can be concluded that the MHSBHE generates improved images with preserving brightness, retaining the shape features of the original histogram and control over enhancement rate.

3.3 The Assessment and Discussion Summary

By visually inspecting the enhanced images and the value of PSNR, entropy and AMBE, it can be summarized that:

(i) Compared to other method MHSBHE technique is the superior method in maximum signal value of the image (PSNR) and high richness of details (entropy) and the degree of brightness preservation (AMBE).

(ii) MHSBHE is robust against the noise compared to other methods which enhance noise during enhancement.

(iii) MHSBHE performs well in high dynamic range images with the low and high illumination.

(iv) MHSBHE, by managing an over-enhancement, can generates images with high quality.

In this proposed method, it generates images with high quality as well as high quantity compared to other literature methods.

4 Conclusion

In this study, the Modified Histogram Segmentation Bi-Histogram Equalization was proposed. In this study, MHSBHE was applied in three steps: histogram modification, histogram segmentation, sub-histogram equalization. The histogram segmentation was modified based on average bins. The main motivation of MHSBHE is that it can handle images automatically with high brightness.

MHSBHE is suitable for a wide variety of images with low-contrast. Also, the proposed method can control various images, automatically. This method attains multi objective of preserving brightness, maintaining the shape features of the original

Fig. 1 the results of Road image by applying different methods.

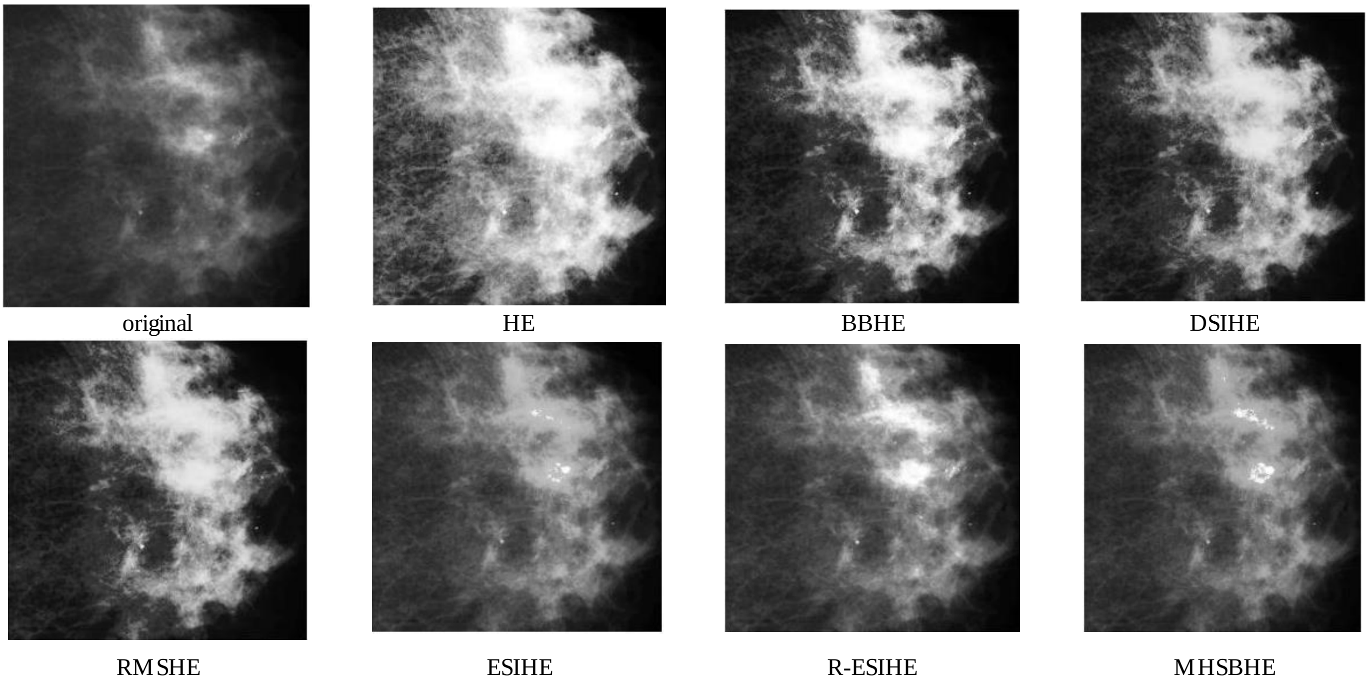

Fig. 2 the results of Mass image by applying different methods.

histogram and controlling over-enhancement rate, suiting for applications of consumer electronics.

MHSBHE eschewed over-enhancement and generated images with natural enhancement. In experimental results, the proposed method was applied on 400 standard images and it outperformed based on four criteria: PSNR, entropy, AMBE and visual assessment. In addition that the results showed that MHSBHE is applicable for consumer electronic products.

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Table 2. Quantitative analyses for six test images.

Test images	PSNR	Entropy	AMBE
Test image Road			
HE	9.9755	5.9461	72.3376
BBHE	15.1492	0.008	27.699
DSIHE	14.693	6.8269	31.9066
RMSHE	15.6982	6.8514	26.4207
ESIHE	19.0273	6.975	22.381
R_ESIHE	18.6507	6.9619	23.0011
MHSBHE	**21.3353**	**6.9877**	**16.9791**
Test image Mass			
HE	10.2326	5.8887	64.2599
BBHE	14.7022	0.0005	20.7681
DSIHE	15.651	6.5896	20.8272
RMSHE	16.2275	6.5724	17.6217
ESIHE	20.9084	6.7167	17.4432
R_ESIHE	20.054	6.6978	18.043
MHSBHE	**22.8458**	**6.7237**	**13.2481**

Table 3 Quantitative analyses from average values of 400 images.

Test images	PSNR	Entropy	AMBE
HE	14.3642	5.18160	29.45891
BBHE	16.9769	0.01453	13.94287
DSIHE	18.8017	5.78793	11.49561
RMSHE	18.6658	5.81110	12.58389
ESIHE	22.6868	5.92269	13.56786
R_ESIHE	21.8907	5.88817	11.83819
MHSBHE	**23.1671**	**5.92385**	**10.95996**